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Adaptive acceleration coefficients for a new search diversification strategy in particle swarm optimization algorithms

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A B S T R A C T

The paper presents a novel paradigm of the original particle swarm concept, based on the idea of having two types of agents in the swarm; the "explorers" and the "settlers", that could dynamically exchange their role in the search process. The explorers' task is to continuously explore the search domain, while the settlers set out to refine the search in a promising region currently found by the swarm. To obtain this particle task differentiation, the numerical coefficients of the cognitive and social component of the stochastic acceleration as well as the inertia weight were related to the distance of each particle from the best position found so far by the swarm, each of them with a proper distribution over the swarm. This particle task differentiation enhances the local search ability of the particles closer to gbest and improves the exploration ability of the particles as the distance from gbest increases.

The originality of this approach is based on the particle task differentiation and on the dynamical adjustment of the particle velocities at each time step on the basis of the current distance of each particle from the best position discovered so far by the swarm.

To ascertain the effectiveness of the proposed variant of the PSO algorithm, several benchmark test functions, both unimodal and multi-modal, have been considered and, thanks to its task differentiation concept and adaptive behavior feature, the algorithm has demonstrated a surprising effectiveness and accuracy in identifying the optimal solution.

1. Introduction

Particle swarm optimization (PSO) is a stochastic computation technique originally developed by Kennedy and Eberhart [27,14]. Although the original intent was to graphically simulate the unpredictable choreography of a bird flock [27], it was quickly realized [14,27,41,42] that the underlying social behavior concept driving each individual or a particle in a swarm could be a powerful population-based, iterative optimization algorithm.

Similar to other evolutionary computation techniques such as genetic algorithms (GAs), in PSO the system is initialized with a population of random individuals (potential solutions, also called particles). However, unlike GAs, individuals are not manipulated according to the rule of survival of the fittest through genetic operators such as selection, crossover and

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mutation, but to each particle is assigned a randomized velocity so that the potential solutions are flown through the search space [14,16,17,27,41–43]. Furthermore, each particle has memory [14] allowing it to keep track of its own best position found so far, as well as of the global best position found so far by the swarm. Therefore, in this situation the optimal solution may be pursued by adjusting the trajectory of each particle toward its own best position (pbest) and toward the current global best position (gbest) discovered by the entire population [14,16,17,27,41–43]. These two acceleration contributions, linked with pbest and gbest, represent the cognitive part and the social part, respectively, of the social cooperation concept underlying the PSO. Nevertheless, the closeness between the crossover operation in genetic algorithms and these two accelerating factors was argued by Eberhart and Shi [15], whereas the similarity between the mutation operator used in evolutionary optimization and these two factors was inferred by Angeline [3].

Particle swarm optimization includes a very simple concept of social cooperation that is easy to implement. Even though early testing found the implementation to be effective in solving several kinds of real-world optimization problems [14,16,17,27,41–43], the standard PSO algorithm frequently suffers from premature convergence toward a local optimum, especially when complex multimodal problems are considered [30,53].

Lack of diversity of the population was recognized early [27] as being the main factor for a premature convergence of the swarm toward a local optimum, thus increasing diversity was mostly considered to be a useful expedient of escaping from local optima [27,30,53]. Unfortunately, increasing the diversity of the swarm is detrimental to fast convergence toward the optimal solution [27,30,53]. The issue is well known because it was demonstrated by Wolpert and Macready [48] that an algorithm cannot outperform all the others on every kind of problem. Therefore, research efforts to improve the performance of an optimization algorithm should not be intended as the search for a general function optimizer [33,48], but rather as the search for a general problem-solver able to perform well on many well balanced real-world benchmark problems [22,46].

Avoiding premature convergence on a local optimum solution without compromising the fast convergence feature of the original PSO formulation is the main reason why several PSO variants have been proposed until now [13]. These approaches comprise fine-tuning of the PSO parameters to control the particle velocity updating [1,4,8,9,39,49,51,53], different variants of the PSO local formulation to take into account the best solution within a local topological neighborhood of particles instead of the entire population [14,28,29,33,45], and hybridization of PSO with other heuristic algorithms [10,19,20,23–25,39,40,50]. The algorithm structure of the modified PSO formulation could become rather elaborate at times, and the reviewed concepts of PSO may also lose the simplicity of the original one.

In this paper, a novel paradigm of the original particle swarm concept has been formulated by drawing inspiration from an early idea suggested by Kennedy and Eberhart [27], even if, initially, it was discarded because it did not show signs of improvement over the well-known PSO version. The idea is that of using two types of agents in the swarm, regarded as "explorers" and "settlers" by Kennedy and Eberhart. The explorers had the task of searching outside the known region of the problem domain, while the settlers had the task of exploring in detail regions that had previously been found to be good. Kennedy and Eberhart implemented this idea through a different way of adjusting their own velocity [27].

It was also observed in [27] that a high value of the cognitive component of the stochastic acceleration related to pbest resulted in excessive wandering of isolated individuals through the search space, while a relatively high value of the social component of the stochastic acceleration related to the gbest brought about premature convergence toward a local optimum. As a result, it was thought that a satisfactory balance between such opposite tendencies could be obtained by multiplying the stochastic cognitive and social components of the acceleration by proper constant coefficients, both of them set at 2 to give them a mean of 1. However, high values of the cognitive component of the stochastic acceleration could allow peripheral particles, above all, to escape from local optima and explore new regions of the search space. On the other hand, a high numerical coefficient of the social acceleration, together with a progressive reduction in the numerical coefficient of the cognitive acceleration as particles get closer to gbest, could significantly increase the swarm attraction toward gbest, thus improving the convergence rate.

The novel paradigm that implements the particle swarm concept is derived from previous remarks and can be summarized as follows. The numerical coefficient of the cognitive component of the stochastic acceleration was not set at 2 over the whole search space, but was progressively increased from zero, when the location of the particle coincided with gbest, to a proper maximum value when the distance of the particle from gbest reached a given value. This was then kept constant for particles that were even more distant from gbest. The numerical coefficient of the social component of the stochastic acceleration was also related to the distance of each particle from gbest, but a different type of distribution over the swarm was adopted. The value of such a coefficient was kept constant and equal to its own maximum value as long as the distance of the particle was less than a given value; then it was progressively decreased according to the distance from gbest. The inertia weight is also dynamically adjusted at each time step by taking into account the distance between particles and gbest: the greater the distance from gbest, the greater the numerical value of the inertia weight, and vice versa.

As a result, the local search ability of a particle will be enhanced as it gets closer to gbest, while the exploration ability of a particle will be improved as the distance from gbest increases. The particles in the outer peripheral of gbest acquire, therefore, a role similar to "explorers", while the particles close to gbest acquire a role similar to that of "settlers" as they are able to perform a better exploitation of the search space around local minima.

Proper values of all numerical coefficients have to be assessed by means of benchmark test functions in order to provide the PSO algorithm with adapting rules. Other adaptive PSO algorithms have recently been suggested [1,4,49,51,53], but none of them assign different tasks to the particles of the swarm, unlike the current paper.